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Stockholm Transit System Potential in 2030

Introduction

Tasked with understanding Stockholm's traffic situation today in light of its continuing population growth, code was used to analyze potential scenarios and interventions. A model was created that can describe the current transport situation and forecast the potential impact that different changes would have. The three specific topics are addressed: (1) the current traffic situation; (2) the effects that an increase in population would have; and (3) potential effects that policy changes could have on the forecasted traffic situation. The first goal was to understand the current traffic situation, which is critical in guiding policymakers and helping them understand use of the current infrastructure and areas for improvement. Second was to understand the impact of increases in Stockholm's population, including the city's placement relative position to other major cities, projected changes in population, and how these factors might affect the transportation system. This analysis considers changes in traffic patterns, the relative share of public transit usage, social-economic changes, and likely effects on congestion. Finally, the analysis examines the potential effects of alternative transport policies and how they may positively or negatively affect traffic patterns. In this case, positive outcomes are measured as increased usage of public transport and "slow" modes of transport. To accomplish all this, the project focused on building a flexible model to describe current transport patterns and possible changes.

The model used many different methods and Python components to address the city's transportation concerns. The coding tasks were broken down into demand modeling, supply modeling, interaction analysis, calibration for car ownership, and policy evaluation. To start, students were provided with a file that included the files Main ("Base"), Landuse, Network, Demand, Assignment, Visualization, and Effect. Students were also provided the Python Environment, Conda ENV - Urban (named "Environment. Socioeconomic data, along with data on the imbalance between where people live (broader city) and where people work (inner city), which critically affects transit and car usage, as also provided. For this analysis, the code focused on the Base, Landuse, Demand, and Effect datasets. For the base data, key variables included fuel cost, fuel consumption, fuel cost per km, parking cost, and transit cost. Furthermore, the parameters settings are shown below. The code also simplified the city into 11 zones, which will be shown later as we compare results. These zones are connected by road and transit networks. Also provided was an initialization of the network, in which car travel time and cost were computed using base conditions. In sum, these files and datasets were captured in the provided code.

Parameter setting

```
######### PARAMETERS ############
alpha = 0.45        # constant for car mode
beta_time = -0.08  # parameter for car travel time
beta_cost = -0.05   # parameter for car travel cost
beta_inv = -0.05    # parameter for transit in-vehile travel time
beta_wait = -0.08    # parameter for transit total waiting time
beta_price = -0.05  # parameter for transit ticket price
beta_slow = -0.5    # parameter for slow mode time
mu = 0.5            # Logsum weight
theta = 1           # parameter for destination choice
param = [alpha, beta_time, beta_cost, beta_inv, beta_wait, beta_price, beta_slow ,mu, theta] # to pass the parameter value to demand function as a list
vot_car = beta_time/beta_cost        # value of time for car
vot_in = beta_inv/beta_price         # value of in-vehile travel time for transit
vot_wait = beta_wait/beta_price      # value of total waiting time for transit
constant = 0.2      # alternative specific constant for owning a car
income = 0.003      # parameter for income
dummy = -0.5        # dummy for residency in the inner city
param_carown = [constant, income, dummy] # to pass the parameter value to landuse function as a list
```

The methods employed focused on travel demand, demand-supply interaction equilibrium, car ownership, and effect evaluation. The first task was to model travel demand. Originally, the code only had a fixed values for selecting a mode to a destination. This was changed to allow the travel demand model to represent different travel choices (i.e. modes) by category of people. This employed a nested logit model, a type of model used to analyze decision-making when choices are nested under one another, i.e., hierarchical.

Changes to the code after the oral assessment: During the assessment, I received guidance focused on four revisions. These four revisions are (1) to change joint probability by using np.multiply concerning the conditional and marginal element-wise probability (ex. np.multiply(m_prob, prob_car) vs. (m_prob* prob_car)), (2) to add the code provided in the announcement on December 13th to the demand function, (3) to change the inner-city from equaling one (note replaced the inner_city element with landuse['citycenter'] in the utility_own equation), and (4) to fix the expected utility equation to weight for population. All of the revisions made in response to this guidance are highlighted in yellow.

The first step in the travel demand calculation was to import the parameters and to reshape the population, car ownership, and employment data. This was done since we found that we had issues with the final total trip count (which should have added up to 800,000). Further edits to the code to adjust for this error will be discussed below. Next was to calculate utility for each mode of transit. These utility calculations are driven by parameters such as cost, travel time, and wait time. Furthermore, v_zone is used to determine the attractiveness of each zone based on the number of employees in the zone. The utility equations are provided below. Note that the model divides the population into two groups: those with access to cars and those without. This is critical as it affects one's set of possible mode options.

```python
# Utilities

v_car = alpha + (beta_time * car_time) + beta_cost * (car_cost + car_park)

v_pt = (beta_inv * inv_time) + (beta_wait * wait_time) + (beta_price * pt_price)

v_slow = beta_slow * dist

v_zone = theta * np.log(emp)
```

Once the utility equations are defined, the next step is to calculate the conditional probabilities, marginal probabilities, joint probabilities, and overall destination utility. Conditional probability, given by code' exp_util_car_mu = np.exp(v_car/mu)', for example, uses mu, a fixed value, to find the probability of choosing the mode given destination. Next, we calculated sum_exp_util by summing the expected utility values calculated previously. Furthermore, 'sum_exp_util' is used to calculate the overall utility, which is the total utility of choosing a destination, used to find marginal probability. To do so, we added the code 'L = np.log (sum_exp_util)' to find Lij, as seen in picture to the right. Using code prob_car = np.divide (exp_util_car_mu, sum_exp_util),' this provides the conditional probability of a mode, car, given utilities of all available modes. First, to find marginal probability, execute the code 'A = v_zone + (mu * L)' and 'A_exp = np.exp(A)' for each zone. In this case, v_zone is the utility component for each zone, mu is a scale parameter, and L is as explained above. This is captured in variable A_exp. Next, using the code provided in the announcement and adjusting the terms to align with our model, B is calculated. (The announced code was 'denom = np.sum(np.exp(Vjm),axis = 1)' and 'denom = denom.reshape(len(denom),1).') The code generates the correct dimension for the probability calculation. It reshapes the array and sums over all destinations for each origin point. Then, to calculate the marginal probability of choosing each destination from each origin (i.e. P(j)), the utility of a destination is divided by the sum of all utilities for an origin. This is as if one was to pick a marble from a bag of ten, there would be a 1/10th probability of choosing a particular marble.

$$e^{V_j + \mu L_j^i}$$

```python
#Overall Des Utility
A = v_zone + (mu * L)
A_exp = np.exp(A)

B = np.sum(A_exp, axis=1)
B = B.reshape(len(B),1)

m_prob = np.divide (A_exp, B)
```

The last probability calculated is joint probability, which is the probability of two or more events happening together. Thus, it represents the probability of an individual choosing a destination within the mode condition. Joint probability is calculated multiplying the conditional probability by marginal probability. These steps are repeated with v_car removed to represent the population without access to a car. These calculations determine the volume of trips for each mode, which are calculated by using the joint probability and taking note of the different population categories using its own function (example, vol_pt = np.multiply (pj_pt, pop_car) + np.multiply(pj_pt_wcar, pop_nocar)).'

The last step in calculating travel demand is to calculate the expected utility using overall destination utility with and without a car. Expected utility is the probability of an event multiplied by the net benefits of the event. In the context of the lab, this is the weighted average of the benefits associated with each transportation mode. Thus, because there are 11 routes in the assignment, there are 11 expected utilities. Furthermore, the EU code incorporates the own and not_own variables related to car ownership during the final step. These corrections permitted weighting for population using the own and not_own variables. Expected utility is calculated using log sum and provides an overall utility measurement for the population given mode choices and destinations. The mathematical format of EU is on the right. Note also the code line 'EU_car = EU_car.reshape(-1, 1) and EU_no_car = EU_no_car.reshape(-1, 1)'. This change was made to ensure that the EU and consumer surplus calculated later would have the shape of a 1D array with 11 elements.

```
EU_car = np.log(np.sum(np.exp(A), axis=1))
EU_no_car = np.log(np.sum(np.exp(A_2), axis=1))

EU_car = EU_car.reshape(-1, 1)
EU_no_car = EU_no_car.reshape(-1, 1)

EU = np.multiply(EU_car, own) + np.multiply(EU_no_car, not_own)
```

$$\ln \sum_{i \in C} e^{\mu V_i} \; .$$

Note the code change below: What is different is the implementation of the weighted population. Version two does this before calculating the log-sum of the exponential of utility, A. This compares to Version three which does this after calculating log-sum. Version four is correct as it treats utility as being independent of the probability of ownership.

Version Two	Version Four
EU_car = np.sum(np.exp(np.multiply(A, own)), axis=1)	EU_car = np.log(np.sum(np.exp(A), axis=1))
EU_no_car = np.sum(np.exp(np.multiply(A_2, not_own)), axis=1)	EU_no_car = np.log(np.sum(np.exp(A_2), axis=1))
EU = np.log(EU_car) + np.log(EU_no_car)	EU = np.multiply(EU_car, own) + np.multiply(EU_no_car, not_own)

The demand code is used for the calculation for the demand-supply interaction equilibrium. The code is shown below.

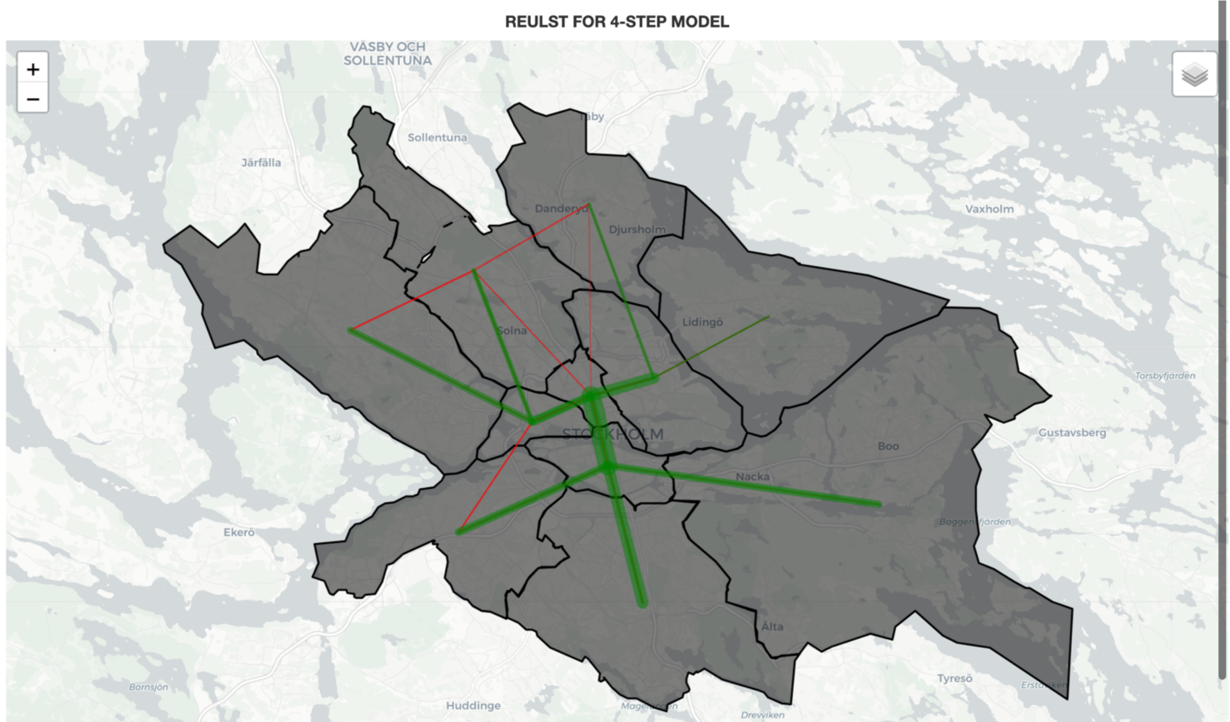
Equilibrium

```
## Suggested Equilibrium cell (also based on the Project file)

# calculate demand
stop = 0
while (stop == 0):
    v_car, v_pt, v_slow, v_zone, EU = Demand(car_time,
                         car_cost,
                         carparking,
                         invt,
                         waitt,
                         transitprice,
                         dist,
                         param,
                         np.array(landuse['pop']).transpose(),
                         np.array(landuse['emp']).transpose(),
                         np.array(landuse['car_ownership']).transpose())
    # save the values of car_time before updating them in Assignment.skim_car

    #old_car_time = ?
    old_car_time = car_time

    # assign the traffic based on the demand to get the new car time, cost, and distance
    G_next_car = Assignment.RouteAssignment(v_car, G_car, origin, destination,vot_car,cost_km)
    G_next_pt = Assignment.TransitAssignment(v_pt, G_pt, origin, destination,vot_in,vot_wait)
    new_car_time, car_cost, car_dist = Assignment.Skim_car(G_next_car, origin, destination, diagnal_dist)

    # calculate car_time values with 0.2 share of new values (from assignemet.skim_car) and 0.8 share of the old car time values
    car_time = (0.8 * old_car_time) + (0.2 * new_car_time) # calculate the travel time

   #define the average error (e.g. 0.2) for convergence, and if it is met, make (stop = 1)
    er = np.absolute(np.mean(car_time)-np.mean(old_car_time)) #average = mean + absolute convers total change

    if (er < 0.2):
        stop = 1 # equilibrium
```

The equilibrium calculation uses a “while” loop that ensures that demand and assignment will be iterated until the exact travel equilibrium times are determined. This uses the demand function and assigns results to the new car time, cost, and distance. The line ‘old_car_time = car_time’ lets us save the current loop travel time before comparing it to the new result, thus checking for equilibrium. Furthermore, the assignment code, which we did not change, uses the new calculations to update the transport network using the new data. Also, the lab notes indicated that we should use a weighted average of the old and new times to stabilize the model. The last step in the equilibrium process is to check the absolute value difference between the new and old car travel times. For example, if these values are less than 0.2 (a desired threshold for a negligible difference) then equilibrium has been reached. The purpose of the demand-supply interaction equilibrium model is to balance the travel demand and assignment transit network (supply). This is important as it enables analysis of traffic patterns and the potential effect of new policies, such as adding new network supply.

The model also calculates car ownership. Car ownership is determined by income levels in the zone and utility of owning a car. Initially, car ownership was fixed at 0.75. However, we were tasked with updating this information in the land use code. Incorporating zone data is also important. For example, people who live in the inner city will likely have a higher income and better access to all transit modes. Furthermore, the car ownership calculation uses a binary logit model where car owners are “1” and non-owners are “0.” A utility function is first calculated using income, inner city, and a constant. The ‘utility_own’ variable, which is the service utility of owning a car based on the parameters, is used to calculate the probability of owning a car by dividing the exponential of the utility of own by itself plus one as it is a binary. When completed, prob_own replaces the fixed car ownership in the land use data. Finally, the land use data is joined by zones, which enables geographical data and the characteristics to be analyzed in combination.

The results are visualized and summarized with the effect and visual codes for the 4-step model. The 4-step model in the project refers to the four steps of (1) trip generation, (2) trip distribution, (3) mode choice, and (4) route assignment, all of which were used in the code. The visualization results are shown below. The map divides the city into 11 zones, with red and green representing road and transit routes, respectively.



The thickness of the line relates to volume usage. This is paired with the summarized created effect code. The effect code also calculated values for externalities (wear and tear accidents, noise emissions - nonco2). These results are shown in the following table. The code and table are essential to the analysis as they help understand the transportation choices and quantify the effects of these choices. This is especially true when comparing policy interventions and future scenarios.

The last two methods used in the model were the forecasting of 2030 data (below) and the code to calculate consumer surplus. Consumer surplus is an economic measurement of perceived consumer benefit. When used, the expected utility of base 2030 and with policy intervention, 2030_1 or 2030_2, is compared and divided by beta_cost to represent the marginal utility of the cost. In the model's context, the expected utility difference reflects how much more or less satisfied consumers are with the different policy interventions. A higher difference in consumer surplus indicates a more significant benefit to consumers.

```
Car Mode Share: 0.4581007924700534
Public Transit Mode Share: 0.5227911893014588
Slow Mode Share: 0.01910801822848784
```

	INFORMATION
Car Volumes	366480
Car Vehicle km Travel (km)	3,039,517
Fuel Used (liter)	258,359
CO2 Emissions (kg)	813,831
CO2 Emissions Cost (sek)	1,220,746
Wear and Tear Cost (sek)	30,395
Accident Cost (sek)	759,879
Noise Cost (sek)	246,201
Total Externalities Cost (sek)	2,269,379
Parking Revenue (sek)	1,832,403
Transit Revenue (sek)	6,273,494
Total Car Trips	366,481
Total Public Transit Trips	418,233
Total Slow Mode Trips	15,286
Total Trips	800,000

Focusing on the city's main characteristics and the transport system highlights what is essential in Stockholm's transit network. The characteristics involved are socioeconomic property, zones, land use, employment, transport network, transit modes, and the factors of these modes. In breaking these down, socioeconomic property is reflected in categories such as car ownership, income, where one lives, and travel behavior. Likewise, zones and land use influence destination attractiveness, population density, and employment locations. The transport network reflects the road and transit network in the city and paths of connectivity across zones. Lastly, transit modes and their factors, such as cost and wait time, influence the model volume of demand and individuals' decisions on transport type. Overall, the project characteristics enable a comprehensive analysis of Stockholm's transport system encompassing transport infrastructure, travel demand patterns, and external factors.

Scenarios and Results Intervention

The model's data was first calculated using a base year of 2020. In 2020, the mode share of car, public transit, and slow mode were 45.81%, 52.28%, and 1.91%, respectively. This served as the baseline scenario for the 2030 scenarios and the two policy intervention scenarios for 2030. For the 2030 baseline, we wrote code assuming an average yearly growth rate of population and employment of 1% and an average yearly growth rate for income of 1.5%. This baseline assumed no policy intervention. Given this, the mode share for 2030 of car, public transit, and slow mode changed to 45.07%, 53.00%, and 1.93%, respectively. Other characteristics, such as total externalities cost, and transit revenue changed between the 2020 and 2030 base scenarios.

Various assumptions were made under these scenarios. These include average yearly growth rates for population, employment, and income. We also made assumptions regarding singular policy interventions and utility equations. We did not adjust the transportation infrastructure, and roads and transit networks did not undergo any expansions (which is probably not realistic).

Furthermore, we assumed that traveler decision-making (i.e., people would make choices considering cost or time factors) and that externalities and variable costs are constant (other than where we choose to intervene). Also assumed is that socio-economic conditions will remain the same and that supply-demand equilibrium will occur. While these are assumptions in the model no doubt differ from real-world conditions, they make the model and forecasting possible under the conditions given. However, it is essential to recognize their limitations and note all assumptions carefully.

The two policy intervention scenarios for 2030 focused on fuel price increases and public transit costs. The first scenario, a change in fuel price, is inspired by the idea that higher fuel prices would decrease people's car use. As noted in *The Gasoline Price and the Commuting Behavior: Towards Sustainable Modes of Transport* by Belloc, studies have found that "higher gasoline prices are related to less commuting by private car, and more commuting by public transport, walking, and cycling" (Belloc, 2022, p. 2). Furthermore, in the Stockholm School of Economics' research on *The Impact of Rising Gasoline Prices on Swedish Households – Is this Time Different?* Andersson analyzed the increase in fuel cost (SEK per liter) from 12 to 20 on car usage. Policy intervention two was inspired by Luxembourg's free transit system as described in *Public Transport - Luxembourg* (Government of Luxembourg). For context, in 2020, Luxembourg made "all modes of public transport" free. The policy's primary goal was to encourage people to use public transport rather than private cars. However, it is essential to note, as the article *One of Europe's Smallest Nations Tries a Big Idea: Free Public Transit* highlights, that while the reaction to the move was positive, it did not automatically reduce car usage. Instead, other actions in combination with free transit need to occur to decrease car dependency, as O'Sullivan states. In the model, accessible public transit was used as an extreme policy intervention to observe what might occur. This meant changing the transit price variable from 15 to 0 in the policy two intervention.

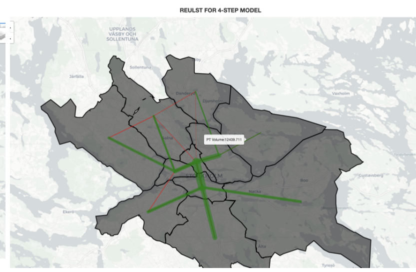
In comparing the different scenarios, base year, and policy interventions, what is essential to consider are mode share of transport, vehicle kilometers traveled by car, external costs, and ticket revenues. The table below presents the data across the four examples.

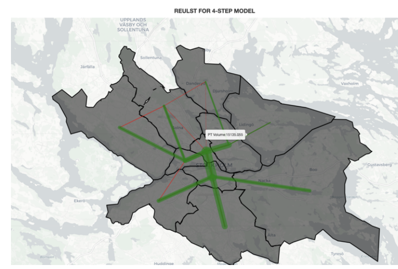
Year	**Base 2020**	**Base 2030**	**Policy 1, 2030**	**Policy 2, 2030**
Car Mode Share	45.81%	45.07%	43.66%	26.44%
Public Transit Mode Share	52.28%	53.00%	54.36%	72.88%
Slow Mode Share	1.91%	1.93%	1.99%	0.68%
Car Volumes	366,480	398,265	385,789	233,630
Car Vehicle km Travel (km)	3,039,517	3,267,739	3,061,941	2,012,907

Fuel Used (liter)	258,359	277,758	260,265	171,097
CO2 Emissions (kg)	813,831	874,937	819,835	538,956
CO2 Emissions Cost (sek)	1,220,746	1,312,406	1,229,752	808,434
Wear and Tear Cost (sek)	30,395	32,677	30,619	20,129
Accident Cost (sek)	759,879	816,935	765,485	503,227
Noise Cost (sek)	246,201	264,687	248,017	163,045
Total Externalities Cost (sek)	2,269,379	2,439,776	2,286,121	1,502,887
Parking Revenue (sek)	1,832,403	1,991,329	1,928,948	1,168,150
Transit Revenue (sek)	6,273,494	7,025,130	7,205,398	0

Using the table, we can determine the following: the share of the population using each mode of transport, vehicle kilometers traveled by car, the costs of externalities like emissions, accidents, and maintenance, and revenues from transit tickets and parking. First, in terms of mode share, in the base 2030 scenario, car mode share will likely decrease while the shares of public transit, and slow mode increase slightly. With policy one intervention, fuel price increases, the policy is predicted only to have a 2% impact on car mode share, thus indicating that, to have a meaningful effect, a larger fuel price increase is needed. More notable is the 20% decrease in car mode share with policy 2, accessible public transit, and the 20% increase in public transit mode. This indicates that public transit costs significantly affect people's demand. Likewise, vehicle kilometers traveled by car are cut by more than 1,000,000 with policy intervention two. This aligns with the changes in mode share. Note, however, that the 200,000 km difference between Base More Senior 2030 and Policy One 2030 indicates that fuel price affects how far people will travel using a car. Similarly, costs of externalities, like emissions, accidents, and maintenance, are also all related to car use. As car mode share decreases, so will the externalities cost, which is also a result of policy intervention two. Lastly, when looking at revenues from transit tickets and parking, transit tickets increased by nearly 1,000,000 sek from 2020 to base 2030, and with policy intervention one. The increase in public transit use results in higher transit revenues. Likewise, parking revenue decreases as car share does. With policy 2, parking revenue also decreases, matching the plummeting car mode share. Of course, there will be no transit revenue for 2030 policy two because the transit cost is now free. The scenario comparisons enable the understanding of how different policies affect traffic patterns.

Comparisons between the scenarios and results of the intervention are also possible by studying the link flows by car and transit and consumer surplus. The three maps below present the link flows by car and transit. While hard to see, the PT volume increases when hovering over different transit routes (green) over the three scenarios. Likewise, when hovering over the red links, they decrease over the three scenarios. Furthermore, the most in-demand road route is centerW to centerN and PT route is centerN to centerS. The least used road route is NE to centerE (except in policy 1 where it is SE to centerS) and the PT route E to centerE.





Base 2030 **Policy 1** **Policy 2**

Furthermore, looking at consumer surplus change, for policy 1, the change compared to base 2030 are the following [0.70818273, 0.8276956, 0.40488866, 0.77162692, 0.69408109, 0.67492959, 0.15928627, 1.78567761, 0.23133799, 0.0110339, 0.23419259]. This is in comparison to policy 2 with [10.56999217, 9.30318106, 11.18233774, 9.58899085, 8.93602992, 9.77034226, 10.53586542, 8.65934529, 10.00042807, 11.10228217, 10.66646095]. As mentioned before, a higher difference in consumer surplus indicates a more significant consumer benefit. Thus, when comparing the two consumer surplus changes, overall, Policy 2 intervention has a more significant positive impact on the consumers than Policy 1. Likewise, this aligns with the dramatic mode share changes between the scenarios. When looking only at consumer surplus change for policy 1, the policy has the highest impact in Zone 8 (NE) with a change of 1.78567761. In contrast, it has a minimal effect, 0.0110339, on Zone 10 (S). Likewise, for the Policy 2 intervention, the most affected Zone 3 (centerS), 11.18233774, and the least affected Zone 8 (NE), 8.65934529. Looking at the map, these zones are aligned and well-connected to Stockholm's public transit system. Overall, the geographic analysis and consumer surplus data reveal a clear trend that policy two intervention enabled a significant positive change in consumer benefits and public transit mode share.

Conclusion

In conclusion, the main finding from the analysis of Stockholm's transport modeling is how potential policy interventions could affect the future traffic situation as the population increases. Under the base scenario for 2030, the model predicts a slight decrease in car mode share and a slight increase in public transit and slow mode shares. However, when policy interventions are applied, this results change. Under policy 1, car mode share declines modestly and public transit usage increases slightly. However, these changes are nothing when compared to the impact of Policy 2. In that case, there is a dramatic decrease in car mode share and a significant increase in public transit when public transit is free. Furthermore, this effect reduces vehicle kilometers traveled and externalities costs. Likewise, parking revenue decreases in all sectors. The data shows that free public transportation significantly affects the population's decision-making for mode more than fuel price increases. However, this could change depending on the level of increase in fuel prices. There are areas for improvement in the results, given the model's limitations and assumptions used. For example, the model does not fully consider constant externalities costs, assumptions of socio-economic conditions, and the lack of infrastructure expansion. Another area for improvement is the model's simplification of Stockholm into 11 zones. Furthermore, when it comes to policy interventions, we only change one factor at a time, whereas in real life, multiple policies could co-occur. Overall, Stockholm has a robust transit system. Currently, most users opt for public transit, followed by using car and slow-mode travel. As the population increases, in 2030 these base patterns would remain the same, with only a modest decrease in car mode share and a slight increase in public transit share. However, policy changes can provide such a solution to create dynamic and dramatic environmental change. The recommendation for the city is to take action to decrease public transit costs, as these are significant factors in consumer preference. However, as the Luxembourg's study revealed, that policy measure should be combined with a city-wide effort to decrease car mode share and increase public transit and slow mode share. Thus, it is recommended to expand slow mode infrastructure, decrease public transit ticket costs, and increase fuel prices. This can occur over time with minor changes from year to year as the city grows. In conclusion, Stockholm should approach such policy changes incrementally while creating more complex modeling tools to consider human behavior.

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